Thailand Statistician
January 2019; 17(1): 30-40
http://statassoc.or.th
Contributed paper

Modelling Motorcycle-Related Head Injury Trends for Thailand Following the 100% Motorcycle Helmet Use Campaign Using Log-linear Model

Mena Patummasut*[a] Nattakorn Phewchean [b],[c] and Jarinratn Sirirattanapa [d]
[a] Department of Statistics, Faculty of Science, Kasetsart University, Bangkok 10900, Thailand.
[b] Department of Mathematics, Faculty of Science, Mahidol University, Rama VI Road, Bangkok, 10400,Thailand.
[c] Centre of Excellence in Mathematics, CHE, Ministry of Education, Bangkok 10400, Thailand.
[d] Department of Otolaryngology, Srinakharinwirot University, Nakhon Nayok 26120, Thailand.
*Corresponding author; e-mail: mena_patummasut@yahoo.com

Received: 16 November 2017
Revised: 1 April 2018
Accepted: 23 May 2018

Abstract

The aim of this paper is to examine trends of motorcycle related head injuries in HRH Princess Maha Chakri Sirindhorn Medical Center, Nakhon Nayok province, Thailand, following the 100% Motorcycle Helmet Use campaign by using log-linear models. Since the injuries count data is overdispersion, the Poisson log-linear model is not reasonable. Consequently, the negative binomial log-linear model accounted for overdispersion is used, and it fits the data very well. The fitted model indicated the increasing trend of head injuries after the 100% Motorcycle Helmet Use campaign was lunched over the years 2011-2016. It is increasing at the rate 1.13% per month.

Keywords: Poisson log-linear model, negative binomial log-linear model, count data.

1. Introduction

Head injuries are a leading cause of death and disability due to traffic accidents involving motorcycles (World Health Organization 2013, 2015). In Thailand, head injuries were the majority of all injuries related to transport accidents, and motorcycles were the largest proportion of traffic injuries. The majority of all injuries related to motorcycle accidents involved head injuries, especially non-helmet wearing motorcyclists (Wibulpolprasert 2002, 2011). It is known that wearing a motorcycle helmet can decrease the risk of death and severe injury. Effective enforcement of motorcycle helmet laws can increase helmet-wearing rates and thereby reduce head injuries (World Health Organization 2015).

The Helmet Act in Thailand was promulgated over the entire Thailand on 1 January 1996. There has been some research assessing the impact of motorcycle helmet legislation on head injuries in Thailand. The pattern of head injuries was studied by analysing trauma patient data from the Songklanagarind hospital. The result was that the severe head injury of admitted patients in this hospital is about 4% decreasing (Phuenpathom et al. 2000). Moreover, the effect of the helmet legislation for motorcyclists in Khon Kean province, Thailand, was studied by investigating the helmet wearing rate, fatalities and severe injuries in the Khon Kean regional hospital during the two years before and after the helmet law (Ichikawa et al. 2003). The result was that after the law was promulgated, helmet-wearers increased five times, while head injuries and deaths decreased about 41%.

Although the motorcycle helmet act was introduced in 1996, the helmet wearing rate remains low and head injuries related to motorcycle accidents is still a serious problem in Thailand. The 100% Motorcycle Helmet Use campaign was launched nationwide in 2011 in order to promote helmet use and to reduce road traffic injuries due to monocycles. From a survey investigating the effectiveness of this campaign, it showed that the motorcycle helmet wearing rate in Thailand had slightly increased from 44% in 2010 to 46% in 2011 after the campaign (Jiwattanakulpaisarn 2012). Moreover, the ThaiRoads Foundation reported that during 2010-2012 Bangkok, the capital city of Thailand, had the highest helmet wearing rate in Thailand at 81% (ThaiRoads Foundation 2013).

The effectiveness of this campaign can be assessed by considering trends of head injuries after the campaign was lunched. If a head injuries has decreasing trend after the campaign started, it could be concluded that the campaign is well effective as the helmet wearing rate would be increasing due to the campaign, resulting in less number of head injuries.

The objective of this research is to investigate trends in motorcycle related head injuries following the 100% Motorcycle Helmet Use campaign. The available head injuries data used in this research is from HRH Princess Maha Chakri Sirindhorn Medical Center, which is the famous medical center located in Nakhon Nayok province, central of Thailand. The analysis of motorcycle related head injuries counts is performed by using log-linear models.

A Poisson regression model called a log-linear model is the generalized linear model for count data. It is a linear model for the log of a Poisson means. When the dependent variables are counts with Poisson distribution, a Poisson regression model should be used to evaluate the relationship between the counts and independent variables (Hoffman 2004). Trends of counts can be investigated by considering the counts in time intervals. A series of counts can be analysed by log-linear models with time as one of the independent variables in the model (Olivier et al. 2013). In Poisson distribution, the required assumption is that the mean is equal to variance, but if the variance is greater than the mean, it is called overdispersion. In the situation of overdispersion, the Poisson log-linear regression model is no longer reasonable. An alternative model dealing with overdispersion is negative binomial log-linear model, which is popularly used for overdispersed count data.

2. Materials and Methods

2.1. Data

To examine motorcycle related head injury trends for Thailand following the 100% motorcycle helmet use campaign launched in 2011, motorcycle related head injuries inpatient admissions data collected from HRH Princess Maha Chakri Sirindhorn Medical Center during the year 2011-2016 was used in this study to analyse the trends of head injuries compared to arm injuries. These admissions have external causes with International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) code V20-Y29, referring to motorcycle rider injured in transport accident, with head injuries (ICD10 code: S00-S09) and arm injuries (ICD10 code: S40-S69). Admission date was also recorded; therefore the number of patients with motorcycle related head injuries can be counted in the specific time interval. According to the above recorded data from the medical center, monthly head and arm injuries admissions were counted as shown in Table 1.

Arm injuries are used as a no-treatment control group compared to head injuries since the 100% helmet use campaign affects and involves only head injuries. Any difference among trends for head and arm injuries over time would exhibit the impact of the 100% helmet use campaign. (Walter et al. 2011).

2.2. Poisson and Negative Binomial Log-Linear Models for Count Data

Suppose the random variable Y_i is a count having a Poisson distribution with mean and variance λ_i. Let X_i be a vector of p independent variables. The Poisson log-linear model can be written as the following form

$$\log(\lambda_i) = X_i'\beta, \tag{1}$$

where β is a vector of p regression coefficients or regression parameters, and $\log(\lambda_i)$ is called the canonical function or the link function. For interpretation, β_j represents the expected change in the log of the mean per unit change in the independent variable X_j, that is, e^{β_j} is the multiplicative effect on λ_i for one unit increase in X_j (Agresti 2002).

Possibly, the term $\log(e_i)$, called an offset, can be included in the model. This term represents the log of some measure of exposure when the dependent variable is a count of events over time or space. Then the model can be written as:

$$\log(\lambda_i) = X_i'\beta + \log(e_i), \tag{2}$$

and it can be written as $\log\left(\frac{\lambda_i}{e_i}\right) = X_i'\beta$, which is the Poisson regression model for rates.

The estimates of the parameters can be obtained by using a maximum likelihood method. The log-likelihood function is

$$\log(L) = \sum\left(y_i \log(\lambda_i) - \lambda_i - \log(y_i!)\right) = \sum\left(y_i X_i'\beta - e^{X_i'\beta} - \log(y_i!)\right). \tag{3}$$

The maximum likelihood estimates can be obtained by taking derivatives of $\log(L)$ with respect to β and setting them to zero yielding then solving the following equation.

$$X'y = X'\hat{\lambda}, \tag{4}$$

where X is the model matrix, y is the dependent variable vector and $\hat{\lambda}$ the vector of fitted values (Dunteman and Ho 2006).

The goodness of fit of the Poisson model can be measured by Pearson's chi-square statistic,

$$\chi_p^2 = \sum \frac{(y_i - \hat{\lambda}_i)^2}{\hat{\lambda}_i}. \tag{5}$$

For large sample of size n, the Pearson's statistic χ^2 is approximately chi-square distribution with $n-p$ degrees of freedom. The overall fit of the models was checked by comparing the Pearson chi-square statistic to the chi-square with $n-p$ degrees of freedom (Dobson and Barnett 2008).

The important assumption of Poisson distribution is that the equality of mean and variance, but when the variance is greater than the mean, it is called overdispersion (Agresti 1996). To investigate overdispersed Poisson data, suppose the variance is proportional to mean, that is, $V(Y_i) = \phi\lambda_i$, where ϕ is a dispersion parameter. If $\phi > 1$, this indicates overdispersion. The dispersion parameter can be estimated by

$$\hat{\phi} = \frac{\chi_p^2}{n-p}, \tag{6}$$

which is the Pearson's chi-square statistic divided by degrees of freedom $n-p$.

Overdispersion causes underestimated standard errors of regression coefficients. In this situation, the Poisson log-linear regression model is not a suitable model anymore. An alternative approach to handle the problem of overdispersion is to use negative binomial log-linear model instead of Poisson log-linear model.

The negative binomial model is a count model allowing for overdispersion. The negative binomial distribution can be derived from the Poisson distribution when the Poisson mean is gamma distributed. To illustrate, suppose Y_i has a Poisson distribution with mean $\lambda_i\gamma_i$. The variable γ_i indicates unobserved variability in counts. Let γ_i be a random variable having a gamma distribution. For convenience, let $\gamma_i \sim Gamma(\delta,\delta)$ with mean $E(\gamma_i)=1$ and $V(\gamma_i)=\frac{1}{\delta}$. Consequently, the gamma mixture of the Poisson distributions gives the negative binomial distribution for Y_i with the probability mass function:

$$P(Y_i = y_i) = \frac{\Gamma(y_i+\delta)}{\Gamma(y_i+1)\Gamma(\delta)}\left(\frac{\delta}{(\lambda_i+\delta)}\right)^{\delta}\left(1-\frac{\delta}{(\lambda_i+\delta)}\right)^{y_i}, \qquad y_i = 0, 1, 2, \dots. \tag{7}$$

The mean of Y_i is $E(Y_i)=\lambda_i$, and the variance of Y_i is $V(Y_i)=\lambda_i+\frac{\lambda_i^2}{\delta}$, where $\frac{1}{\delta}$ is the dispersion parameter (Hilbe 2011). When $\frac{1}{\delta}$ is equal to zero, Y_i has Poisson distribution. If $\frac{1}{\delta}>0$, then the variance is larger than the mean, so the negative binomial distribution is overdispersed relative to the Poisson. It is known that the negative binomial distribution is the distribution of the number of failures before the r^{th} success in a sequence of independent Bernoulli trials with the probability of success p. The probability mass function of Y_i in (7) is the negative binomial probability function where $r=\delta$ and $p=\frac{\delta}{\lambda_i+\delta}$.

For the negative binomial modelling, the log link could be used in the same way as the Poisson model (McCullagh and Nelder 1989). The negative binomial model including an offset can be written as:

$$\log(\lambda_i) = \mathrm{X}_i'\beta + \log(e_i).$$

To estimate the parameters by using a maximum likelihood method, the log-likelihood is

$$\log(L) = \sum\left(\delta\log(\frac{\delta}{\lambda_i+\delta}) + y_i\log(\frac{\lambda_i}{\lambda_i+\delta}) + \log\Gamma(y_i+\delta) - \log\Gamma(y_i+1) - \log\Gamma(\delta)\right). \tag{8}$$

Taking the first-order and second-order derivatives of $\log(L)$ and equating them to zero yield the following likelihood equations:

$$\sum_{i=1}^{n}\frac{x_{ij}(y_i-\lambda_i)}{1+\delta^{-1}\lambda_i}=0 \qquad j=1, 2, \dots, k, \tag{9}$$

$$\sum_{i=1}^{n}\left(\delta^2\left[\ln(1+\delta^{-1}\lambda_i)-\sum_{j=0}^{y_i-1}\frac{1}{j+\delta}\right]+\frac{y_i-\lambda_i}{\delta^{-1}(1+\delta^{-1}\lambda_i)}\right)=0. \tag{10}$$

The maximum likelihood estimates can be obtained by solving these equations. The estimated dispersion parameter, denoted as $\hat{\delta}^{-1}$, can be calculated from (10), but it requires iterative methods (Lawless 1987).

For model validation in a negative binomial model, the Pearson and deviance residuals are considered. The Pearson residual is

$$r_i = \frac{y_i - \hat{\lambda}_i}{\sqrt{\text{var}(Y_i)}} = \frac{y_i - \hat{\lambda}_i}{\sqrt{\hat{\lambda}_i + \hat{\lambda}_i^2 \delta^{-1}}}, \tag{11}$$

and the Pearson chi-square statistic is

$$\sum_{i=1}^{n} r_i^2 = \sum_{i=1}^{n} \frac{\left(y_i - \hat{\lambda}_i\right)^2}{\left(\hat{\lambda}_i + \hat{\lambda}_i^2 \delta^{-1}\right)}, \tag{12}$$

which is the sum of squares of the Pearson residuals (Agresti 2002). For a large sample of size n, it is approximately chi-square distribution with $n-p$ degrees of freedom, so it can be used for model assessment. The deviance residual is

$$\hat{\varepsilon}_i = (\text{sign}(y_i - \lambda_i))d_i, \tag{13}$$

where d_i is the contribution of the i^{th} observation to the deviance, denoted by D and defined as

$$D = 2\sum_{i=1}^{n} \left(\log(L(y_i; y_i)) - \log(L(y_i; \lambda_i))\right), \tag{14}$$

where $\log(L(y_i;\lambda_i))$ is the log-likelihood function in (8), and $\log(L(y_i; y_i))$ is the log-likelihood function with y_i replacing λ_i. For the negative binomial model, the deviance is

$$D = \sum_{i=1}^{n} d_i^2,$$

where

$$d_i^2 = \begin{cases} 2\left(y_i \log\left(\frac{y_i}{\lambda_i}\right) - \left(y_i + \delta\right)\log\left(\frac{1 + y_i\delta^{-1}}{1+\delta^{-1}\lambda_i}\right)\right) & \text{if } y_i > 0 \\ 2\delta \log\left(1 + \delta^{-1}\lambda_i\right) & \text{if } y_i = 0. \end{cases} \tag{15}$$

The smaller the deviance, the better the model. For a large sample of size n, the deviance is approximately chi-square distribution with $n-p$ degrees of freedom, thus it can be used to test the goodness of fit of the model (Zwilling 2013).

The assumptions of homogeneity, independence and normality of residuals must be met. The residuals should be independent, have a distribution which is approximately normal with a mean of zero and have a constant variance (Dobson 2002, and Hoffman 2004). To check the homogeneity assumption, a plot of the residuals versus fitted values can indicate homogeneity. If there is no pattern in this graph, then this assumption is met. Graphical analysis of normality is performed by using the normal quantile-quantile (Q-Q) plot. The points in the plot should fall on or near the straight line representing normality; otherwise, the normality assumption is not met. To check the independence of residuals, a plot of residuals against a time variable is considered. Residuals should fluctuate randomly with no pattern. An upward or downward trend indicates that the residuals are not independent.

Unlike the Poisson regression, the negative binomial regression does not require the equality of the mean and variance assumption. For small dispersion, the negative binomial model approaches the

Poisson model. The negative binomial model has the greater estimated variance indicating the overdispersion uncaptured with the Poisson model.

3. Results and Discussion

Firstly, the Poisson log-linear model of hospital admission counts of head and arm injuries related to motorcycle was performed. Let Y_i be the admission counts for head and arm injuries on month i having Poisson distribution with mean λ_i. The Poisson log-linear model has the following form:

$$\log(\lambda_i) = \beta_0 + \beta_1 TIME_i + \beta_2 INJURY_i + \beta_4 TIME_i \times INJURY_i + \log\left(POP_i\right), \quad (16)$$

where *TIME* represents monthly intervals defined using the date of admission and was treated as continuous covariate. *INJURY* is an indicator variable that takes on the values 0 for arm injuries and 1 for head injuries. *POP* is monthly population size in this province used as the measure of exposure.

To investigate trends of head and arm injuries, the independent variable *TIME* is included in the model. To inspect the difference of level of head and arm injuries, the variable *INJURY* is included in the model. To compare head injuries trend to arm injuries trend, the interaction term $TIME \times INJURY$ is included in the model. In this study, Nakhon Nayok province population size was considered as measure of exposure to account for changes in population size. Monthly population estimates as shown in Table 2 were interpolated from yearly population (Bureau of Registration Administration 2017).

For interpretation, β_0 indicates the level of arm injuries, β_1 describes the monthly rate of change or trend in arm injuries, β_2 exhibits the difference of level of head and arm injuries and β_3 is a measure of how the monthly change in head injuries differs from arm injuries.

The result of the fitted Poisson model is shown in Table 3. The overall fit of the model was assessed by comparing the Pearson's chi-square statistic to the chi-square distribution with degrees of freedom given by the total number of parameters minus the number of parameters estimated. Unfortunately, the model does not fit because the Pearson's chi-square statistic was significant at the 0.05 level with p-value less than 0.0001. Moreover, the dispersion parameter estimate is, Pearson's chi-square statistic divided by degrees of freedom, 357.24/140 = 2.55 indicating overdispersion. To deal with overdispersion, the negative binomial log-linear model is used.

Let Y_i be the admission counts for head and arm injuries having a Poisson distribution with mean $\lambda_i \gamma_i$ and let $\gamma_i \sim Gamma(\delta, \delta)$. Now, Y_i has the negative binomial distribution with $E(Y_i) = \lambda_i$. The negative binomial log-linear model has the form same as (16).

The result of the fitted negative binomial model is shown in Table 4. The test of the Pearson's chi-square statistic was not significant at the 0.05 level with the p-value of 0.42. Thus, the negative binomial log-linear model fits the data very well. Also, the deviance statistic was not significant at the 0.05 level with p-value 0.34, indicating model fits the data. The dispersion estimate is δ^{-1} = 0.0545, which is rather large comparing to its standard error of 0.0109.

For model validation, the assumptions of homogeneity, independence and normality of the deviance residuals are checked by examining the plot of the deviance residuals versus fitted values in Figure 1(a), the plot of the deviance residuals versus Time in Figure 1(b), and the Q-Q plot of the deviance residuals in Figure 1(c). Since the plot of the deviance residuals versus fitted values has no pattern, the homogeneity assumption of the deviance residuals is met. From the plot of the deviance residuals versus Time, the deviance residuals fluctuate randomly with no pattern, so the independence assumption of the deviance residuals is satisfied. From the Q-Q plot, the points in the plot fall on the line indicating normality. Therefore, the assumptions of homogeneity, independence and normality of the deviance residuals are met.

The monthly head and arm injuries counts from Table 1 are plotted as shown in Figure 2. It can be seen that both injuries have increasing trend, and head injury counts are slightly lower than arm injury counts. From the result of the fitted model in Table 4, the coefficient estimate of *TIME* is $\hat{\beta}_1 =$ 0.0113 significant at 0.05 level indicating that arm injuries has significantly increasing trend at the rate $(e^{0.0113}-1)\times 100\%$ = 1.13% per month. The coefficient estimate of *INJURY* is $\hat{\beta}_2 = -0.047$, which is not significant at 0.05 level, describing that there is no difference of level of head and arm injuries. In addition, the coefficient estimate of *TIME*×*INJURY* is $\hat{\beta}_3 = -0.0043$, which is not significant at 0.05 level, meaning that the monthly change in head injuries does not significantly differ from arm injuries. It can be concluded that both injuries have the same increasing trend at the rate of 1.13%.

Table 1 Motorcycle-related head and arm injuries admission counts for 2011-2016

Month	2011		2012		2013		2014		2015		2016	
	head	arm	head	arm	head	arm	head	arm	head	arm	head	arm
Jan	32	32	25	26	25	34	21	25	13	20	33	43
Feb	26	15	25	28	15	24	20	21	22	24	44	53
Mar	18	11	27	23	23	29	21	31	26	37	54	62
Apr	20	17	12	16	9	13	13	23	24	27	27	47
May	19	9	28	24	20	20	17	22	29	38	37	38
Jun	22	22	17	27	19	36	24	31	40	47	25	37
Jul	18	16	23	40	16	17	14	18	21	37	25	30
Aug	25	22	28	28	20	25	11	25	20	33	25	52
Sep	15	20	24	30	18	27	24	26	19	32	45	60
Oct	26	35	26	42	16	24	29	27	36	36	37	43
Nov	24	37	26	22	17	35	25	24	30	46	45	58
Dec	29	39	25	27	26	34	21	14	42	54	43	61

Table 2 Monthly population estimates in Nakhon Nayok province for 2011-2016

Month	2011	2012	2013	2014	2015	2016
Jan	254,482	255,368	256,257	257,142	258,031	258,913
Feb	254,557	255,443	256,333	257,216	258,104	258,988
Mar	254,626	255,515	256,399	257,286	258,172	259,058
Apr	254,705	255,590	256,480	257,359	258,245	259,134
May	254,775	255,662	256,548	257,434	258,318	259,207
Jun	254,848	255,738	256,626	257,509	258,393	259,282
Jul	254,922	255,811	256,695	257,582	258,466	259,358
Aug	254,996	255,885	256,778	257,657	258,542	259,430
Sep	255,072	255,961	256,846	257,734	258,618	259,505
Oct	255,148	256,033	256,919	257,804	258,689	259,577
Nov	255,220	256,109	256,999	257,882	258,765	259,653
Dec	255,293	256,182	257,067	257,955	258,838	259,726

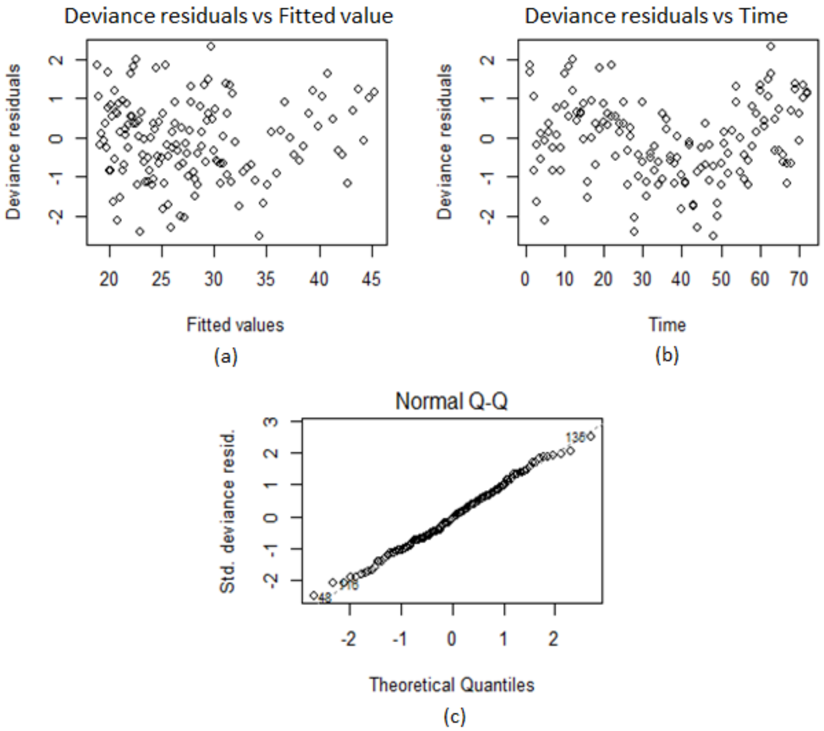

Figure 1 The plot of the deviance residuals versus fitted values (a), the plot of the deviance residuals versus Time (b), and the normal Q-Q plot of the deviance residuals (c)

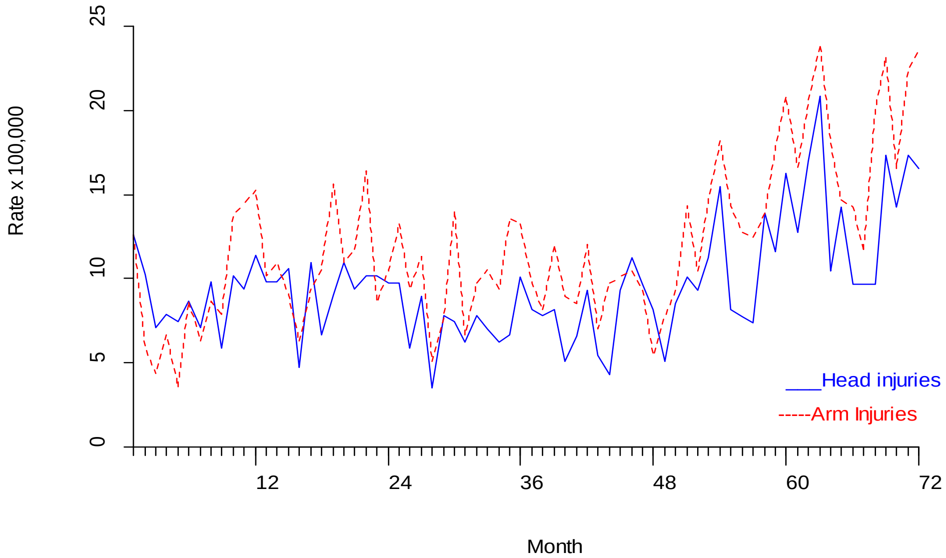

Figure 2 Rates per 100,000 population of motorcycle-related head and arm injuries admissions in HRH Princess Maha Chakri Sirindhorn Medical Center by month in 2011-2016

Table 3 Poisson log-linear model estimates

Variable	Estimate	Standard error	95%CI	p-value
Intercept	-9.4914	0.0482	-9.5859, -9.3969	<0.0001
TIME	0.0119	0.0010	0.0099, 0.0139	<0.0001
INJURY	-0.0456	0.0706	-0.1839, 0.0928	0.5184
TIME×*INJURY*	-0.0043	0.0015	-0.0073, -0.0013	0.0054
Pearson chi-square statistic is 357.24 (df=140)				<0.0001

Table 4 Negative binomial log-linear model estimates

Variable	Estimate	Standard error	95%CI	p-value
Intercept	-9.4674	0.0725	-9.6095, -9.3253	<0.0001
TIME	0.0113	0.0017	0.0081, 0.0145	<0.0001
INJURY	-0.0470	0.1034	-0.2496, 0.1557	0.6496
TIME×*INJURY*	-0.0043	0.0024	-0.0089, 0.0003	0.0697
Pearson chi-square statistic is 142.77 (df=140)				0.4200
Deviance statistic is 146.19 (df=140)				0.3400
Dispersion	0.0545	0.0109		

From the analysis result, head injuries has an increasing trend same as with arm injuries at the rate of 1.13% per month. This means that the helmet use campaign does not affect head injuries. It can be implied that the campaign does not significantly lower head injuries. The reason for the increasing rate of head injuries may be a result of the decrease in the helmet wearing rate in Nakhon

Nayok province during the years 2011-2016 as shown Table 5 (ThaiRoads Foundation 2016). Notice that helmet wearing rate of Nakhon Nayok province is lower than that of the entire country.

Table 5 Helmet wearing rate in Thailand for 2011-2016

Year	Thailand	Nakhon Nayok province
2011	46%	46%
2012	43%	42%
2013	43%	40%
2014	42%	41%
2015	43%	35%
2016	43%	32%

This paper provided the reasonable model for motorcycle-related head injuries from HRH Princess Maha Chakri Sirindhorn Medical Center, Nakhon Nayok province, Thailand, following the 100% Motorcycle Helmet Use campaign. This obtained model is useful for investigating the trend of head injuries due to motorcycles after such campaign was lunched. Consequently, the effectiveness of this campaign can be evaluated. Since the campaign was launched nationwide, this model could be prototype model to apply with head injuries data from other hospitals in Thailand.

4. Conclusions

The objective of this paper is to investigate the trend in motorcycle related head injuries in HRH Princess Maha Chakri Sirindhorn Medical Center, Nakhon Nayok province, Thailand, following the 100% Motorcycle Helmet Use campaign. Since the injuries count data is overdispersion, the Poisson log-linear model is not reasonable. Consequently, the negative binomial log-linear model accounted for overdispersion is used, and it fits the data very well. The fitted model shows the increasing trend of head injuries after the 100% Motorcycle Helmet Use campaign was launched over the years 2011-2016 at the rate of 1.13% per month. It looks like the campaign does not significantly lower head injuries. The reason of increasing in head injuries might be the decrease of helmet wearing rate in Nakon Nayok province during the years 2011-2016.

Acknowledgements

The second author is supported by the Centre of Excellence in Mathematics, CHE, Thailand.

References

Agresti A. An introduction to categorical data analysis. New York: Wieley; 1996.

Agresti A. An introduction to categorical data analysis, 2nd edition. New York: Wieley; 2002.

Bureau of Registration Administration, Department of Provincial Administration, Ministry of Interior, Thailand. Population from registration recorded by province. 2017 [cited 2017 Nov 15]. Available from: http://stat.bora.dopa.go.th/stat/

Dobson AJ. An Introduction to Generalized Linear Models. Boca Raton: Chapman & Hall/CRC; 2002.

Dobson AJ, Barnett AG. An introduction to generalized linear models. 3rd edition. Boca Raton: Chapman & Hall/CRC; 2008.

Dunteman GH, Ho MR. An introduction to generalized linear models. California: Thoundsand Oaks, Sage Publications; 2006.

Hilbe J. Negative binomial regression, 2nd edition. New York: Cambridge University Press; 2011.

Hoffman J. Generalized linear models. Boston: Pearson Education Inc; 2004.

Ichikawa M, Chadbunchachai W, Marui E. Effect of the helmet act for motorcyclists in Thailand. Accid Anal Prev. 2003; 35: 183-189.

Jiwattanakulpaisarn P. Effectiveness of the 100% motorcycle helmet use campaign in Thailand. Inj Prev. 2012; 18: A1-A246.

Lawless JF. Negative binomial and mixed Poisson regression. Can J Stat. 1987; 15: 209-225.

McCullagh P, Nelder J. Generalized linear models, 2nd edition. London: Chapman & Hall; 1989.

Olivier J, Walter SR, Grzebieta, RH. Long term bicycle related head injury trends for New South Wales, Australia following mandatory helmet legislation. Accid Anal Prev. 2013; 50: 1128-34.

Phuenpathom N, Tiensuwan M, Ratanalert S, Saeheng S, Sripairojkul B. The changing pattern of head injury in Thailand. J Clin Neurosci. 2000; 7: 223-225.

ThaiRoads Foundation. Thailand Motorcycle Helmet Use 2010-2012. 2013 [cited 2017 Nov 15]. Available from: http://www.trso.thairoad.org/resources/5026.

Thairoads Foundation. Thailand Motorcycle Helmet Use 2016. 2016 [cited 2017 Nov 15]. Available from: http://www.thairoads.org/projects/4021.

Walter SR, Olivier J, Churches T, Grzebieta R. The impact of compulsory cycle helmet legislation on cyclist head injuries in New South Wales. Accid Anal Prev. 2011; 43: 2064-71.

Wibulpolprasert S. Thailand Health Profile 1999-2000. Bangkok: Express Transportation Organization Publishing; 2002.

Wibulpolprasert S. Thailand Health Profile 2008-2010. Bangkok: Veteran Press; 2011.

World Health Organization. Global status report on road safety 2013: supporting a decade of action. 2013 [cited 2017 Nov 15]. Available from: https://www.iru.org/apps/cms-filesystem-action/policies/ sustainable_development/ road_safety/gsrrs_en.pdf

World Health Organization. Road safety in the south-east Asia region. 2015 [cited 2017 Nov 15]. Available from: http://www.who.int/violence_injury_prevention/ road_ safety_ status/2015/ Road_Safety_SEAR_3_for_web.pdf

Zwilling ML. Negative binomial regression. Math J. 2013; 15: 1-18.